Condition Based Maintenance for Light Trucks

Janos Grantner, Bradley Bazuin, Liang Dong and Jumana Al-shawawreh
Department of Electrical and Computer Engineering
Richard Hathaway and Claudia Fajardo
Department of Aeronautical and Mechanical Engineering
Western Michigan University, Kalamazoo, MI 49008, USA
janos.grantner@wmich.edu

Matthew P. Castanier and Shabbir Hussain
US Army RDECOM-TARDEC
Warren, MI 48397-5000, USA
matt.castanier@us.army.mil

***Abstract*—Army ground vehicles often operate in extremely severe environmental and battlefield conditions. There are challenges for the reliability of the military ground vehicle fleet, which need to be addressed. Condition Based Maintenance (CBM) allows maintenance to be performed based on evidence of need provided by reliability modeling and/or other enabling technologies, thus reducing maintenance costs and increasing vehicle availability. The architecture of the Intelligent Vehicle Health Management System (IVHMS) for light trucks is presented. A fuzzy model is developed to diagnose the axle fatigue of the vehicle. The extraction of the fuzzy rules is based upon expert knowledge and a linear damage model. Training data will be used to modify the membership functions and the fuzzy If-Then rules to improve the quality of the fuzzy model for fault diagnostics. The improvement of the fuzzy model will be carried out using re-clustering operation and membership function optimization.**

***Keywords*—Condition Based Maintenance, fuzzy model, axle fatigue, intelligent diagnostics, linear damage model, membership function optimization, clustering extraction and re-clustering.**

I. INTRODUCTION

The ever increasing roles the U.S. Army play in the global defense of our nation's security have seen the Army ground vehicles operating in extremely severe environmental and battlefield conditions. There are challenges for the reliability of the military ground vehicle fleet, which need to be addressed. The Army intends to use computer based modeling and simulation to address these challenges. Reliability and safety computer simulations provide state-of-the-art tools to predict the reliability and safety of fielded trucks in off-design scenarios and physics-based prognostics criteria needed for condition-based maintenance (CBM) systems. CBM allows maintenance performed on evidence of need provided by the enabling reliability modeling, thus increases vehicle availability. A self-powered, cost-efficient, integrated intelligent system of sensors and microcontrollers for vehicle health monitoring is desired.

A significant segment of the Army's Light Tactical Vehicle Fleet is not equipped with any digital electronics that could directly contribute to CBM. Therefore it seems justifiable to develop a vehicle health management system from the ground up.

In this paper, recent research is described that is part of a larger effort to develop an Intelligent Vehicle Health Management System (IVHMS) for light trucks, with important future applications to military light tactical vehicles. In particular, this paper is focused on the system architecture for engine and axle monitoring and the development of a fuzzy model for axle fatigue damage. A commercial light truck has been chosen as an experimental vehicle platform.

The rest of the paper is organized as follows: in Section 2, the architecture and the main functions of the IVHMS are presented. In Section 3, recent research results in the area of vehicle diagnostics are summarized. In Section 4, the concept of fatigue damage is described. In Section 5, a fuzzy model for fatigue damage is introduced. In Section 6, the generation of the fuzzy rules is described. In Section 7, the approach to optimize the membership functions is briefly explained. Conclusions are given in Section 8.

II. IVHMS ARCHITECTURE

The functional block diagram of the Intelligent Vehicle Health Management System (IVHMS) is depicted in Fig. 1.

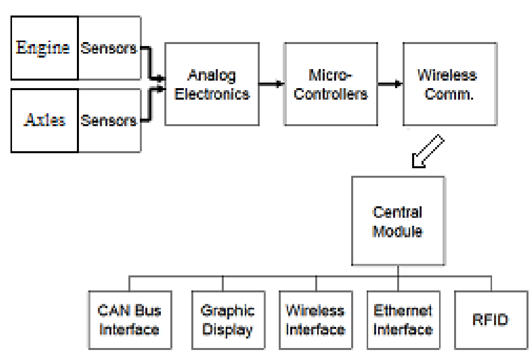

Figure 1. System block diagram

With respect to the engine, the focus is to diagnose a potential power loss. The following parameters have been

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14. ABSTRACT
Army ground vehicles often operate in extremely severe environmental and battlefield conditions. There are challenges for the reliability of the military ground vehicle fleet, which need to be addressed. Condition Based Maintenance (CBM) allows maintenance to be performed based on evidence of need provided by reliability modeling and/or other enabling technologies, thus reducing maintenance costs and increasing vehicle availability. The architecture of the Intelligent Vehicle Health Management System (IVHMS) for light trucks is presented. A fuzzy model is developed to diagnose the axle fatigue of the vehicle. The extraction of the fuzzy rules is based upon expert knowledge and a linear damage model. Training data will be used to modify the membership functions and the fuzzy If-Then rules to improve the quality of the fuzzy model for fault diagnostics. The improvement of the fuzzy model will be carried out using re-clustering operation and membership function optimization.

15. SUBJECT TERMS
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selected for measurement: engine output torque, throttle position, crankshaft rotational speed, exhaust gas temperature, pressure drop across the intake air filter, and intake air temperature. The throttle position sensor will monitor the driver's input. The output torque and rotational speed will be measured to calculate the engine output power. Exhaust gas temperatures will be recorded simultaneously to identify whether any significant change in the engine's output power is a cylinder-specific problem or a global problem. This information is important to narrow down potential causes. At this point we consider only one global problem, blockage of the intake air filter.

Suspension and structure based maintenance might best be categorized as maintenance required due to operation at, or near the limits of the operating envelope. To assess the levels within the maintenance required category, the best methodologies might be to determine whether 1) it is routine maintenance, 2) limits exceeded, disassemble and inspect, 3) limits exceeded replace after mission complete, and failure imminent.

Structure and drive train initiatives have taken on the concept of determining the magnitude of the initial load and detect both primary and secondary results of that impact. Detecting the best location and determining the best methodologies are key for determining those primary and secondary factors. Terrain damaging impact which could be generated from the surface terrain or from under surface detonation type devices induce high wheel loads. The potential for damage can be inferred from the measurement of such loads. The assumption has been made that the best location to sense both magnitude and direction is at the spindle/axle location closest to the wheel.

Damage that occurs can be either instantaneous or cumulative in nature; therefore the best prediction system should take into account magnitude and direction, as well as frequency.

To sense the primary loads simple commercially available rosette, and simple, single axis strain gages are used. Through electronically selected configurations, 3-axis loads and 3-axis torques are available. One additional parameter, the thermal induced strain, will allow the tracking of temperature to provide the secondary damage assessment. A functional block diagram of the axle sensor board is shown in Fig. 2. Three analog channels of the external 24-bit Analog to Digital Converter chip are dedicated to measure the voltages generated by Wheatstone bridges that are made up of strain gages and precision resistors. The bridges can be configured as full, half, or quarter bridges to allow various strain gage configurations. The bridge voltages are amplified through an instrumentation amplifier to utilize the full operating range of a 24-bit Digital to Analog Converter chip. The fourth analog channel is used to interface to a thermocouple. The ADC chip is hooked up to the Serial Peripheral Interface (SPI) port of the microcontroller.

The Zigbee transceiver chip is also connected to the microcontroller via a serial interface. In addition, four digital ports are also available. This axle sensor board architecture is a good representation to the other sensor board architectures as well.

All the electronic parts considered are off-the-shelf devices to leverage existing technologies and reduce cost. The microcontroller interfaced to the sensors provides for primary data manipulation/filtering and local data storage. Time stamps are attached to the sensory data collected at given intervals. In addition, the microcontroller firmware provides for off-loading the collected data via short-range wireless communications to a central data storage module located in a

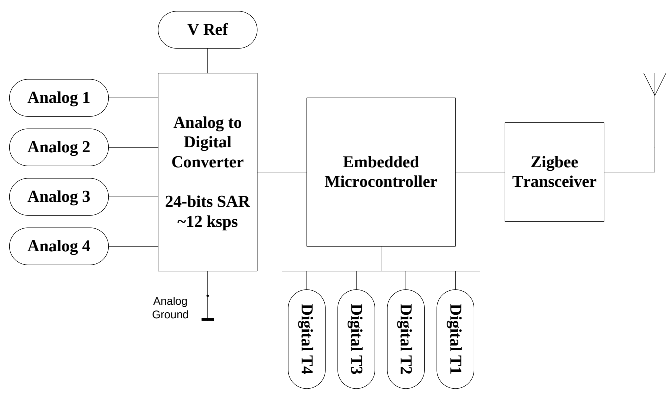

Figure 2. Block diagram of the axle sensor board

safe place on the vehicle. The sensor modules will communicate with each other and with the central data module via a wireless CAN that is compliant with the IEEE 802.15 protocol. The wireless personal area network is implemented using the ZigBee protocol. Due to the chosen network topology, sensor modules can relay data generated at far away sensor modules towards the central data module. This capability guarantees a minimum transmission load on the system, power-efficiency and data security. The central data module integrates all data collected from the intelligent sensors attached to the various vehicle systems. A rugged laptop computer is used as the central data module. On demand, the central data module will upload its data along with the vehicle ID Number via another, secure short range wireless communications link, or via a wired Ethernet port to a mobile device (e.g., another laptop computer authorized for CBM). In addition, a CAN Bus interface is also available for vehicles that are equipped with a CAN Bus-based sensor system in order to collect that data as well. The RFID module allows the electronic tracking of the vehicle when it leaves or enters a staging area.

The central data module will perform basic monitoring functions based upon the sensed data and preset boundary values. If the sensed data reveals a critical situations in the status of the vehicle then alarm signals will be generated in real-time on the laptop computer's screen. In addition, the

coordinator module will have sufficient nonvolatile memory to store the sensory data on the vehicle over a long mission route.

The diagnosis and prognosis of the vehicle health will be based upon both the data uploaded from the vehicle's central data module and a database containing failure mode data on the same vehicle and other vehicles of the same class of vehicles. The diagnosis part will attempt to assess the status of failing, or failed components of vehicle systems by the method of triangulating sensor information on the component as well as using measurement records of healthy and failed components. An intelligent diagnostic system is being developed using both analytical methods and fuzzy logic. A limited, rudimentary version of the diagnostics system will be provided on the screen of the central data module laptop computer.

The prognostics feature will also be based upon actual vehicle data and a recorded vehicle failure data archive. Using fuzzy logic an intelligent system will be proposed that will infer qualitative predictions on the mission reliability of the vehicle to some time periods into the future.

III. MODELS FOR VEHICLE DIAGNOSTICS

Analytical modeling of vehicles using the finite element method is typically too computationally expensive for real time diagnostics. In addition, important model parameters may not be readily available. Furthermore, the most useful information is often the engineer's domain knowledge and the run-time data collected on the vehicle for a long period of time. Fuzzy models are flexible and allow uncertainty in the values of the control variables of the fault diagnostics.

In the fuzzy model, the control variables are usually defined using linguistic terms such as "Low," "Medium," etc., where these fuzzy terms are represented by membership functions. The membership functions are uniquely defined by a set of critical parameters.

The fuzzy rules and fuzzy membership functions are often generated on the basis of expert knowledge. Training data are also key for fuzzy rule extraction using cluster extraction operations. There are many known clustering methods that can be used to extract fuzzy rules. Filev and Angelov [1] showed the suitability of a density-based method. It stems from mountain/subtractive clustering to a non-stationary process with relatively fast dynamics. They also showed the suitability of the distance-based clustering method for a zero-order Takagi-Sugeno model. Filev and Tseng [2] applied the k-Nearest Neighbor clustering method for modeling and prediction of machine health status. Lu, Chen, and Hamilton [3] used clustering extraction and re-clustering operations to extract the fuzzy rules in order to detect a vacuum leak in an electronic engine controller.

A fuzzy model will be used to diagnose the fatigue of the vehicle's axle and to estimate the remaining lifetime of the vehicle based upon the cumulative damage to the axle. In this research, the initial fuzzy model and the fuzzy rule base for fatigue diagnostics will be generated using expert knowledge and the linear damage model.

Optimization of the membership functions and the fuzzy rules is necessary to improve the quality of the fuzzy model for fault diagnostics.

IV. FATIGUE DAMAGE

Fatigue damage occurs when a material or structure is subject to cyclical or repeated loading. Each cycle inflicts a small amount of damage and as the load repeats the damage begins to build up to cause cumulative damage. When the cumulative damage builds up to a point that the material cannot stand any longer the fatigue damage occurs. Every structure has a fatigue life, or an estimated length of time for which the structure can maintain integrity before failing due to fatigue damage [4].

For each stress load there is maximum number of cycles N_f that the material can stand before the fatigue damage takes place. The relation between the stress S and the number of cycles to failure is usually given as the S-N curve [4]. The S-N curve for an axle is shown in Fig. 3.

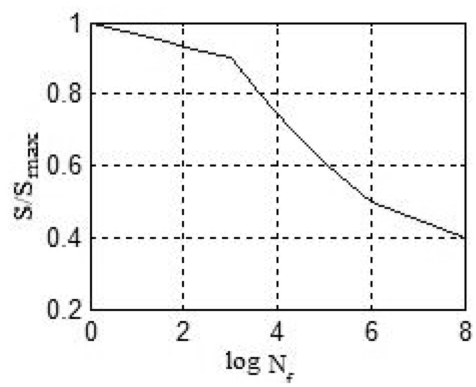

Figure 3. S-N curve of an axle

There are several models available in the literature to calculate the cumulative damage D_c of the material based on the S-N curve like the ones proposed by Subramanyan, Hashin, and Manson and the linear damage method [5].

The linear damage model assumes that there is a unique linear relationship between the cycle fraction ($n_i / N_{i,f}$) and the material damage regardless of the stress level. Then the cumulative damage can be calculated as follows:

$$D_c = \sum_{i=1}^{n} \frac{n_i}{N_{f,i}} \tag{1}$$

When the cumulative damage reaches 1 (i.e., $D_c = 1$) the fatigue damage occurs.

V. FUZZY MODEL FOR FATIGUE DAMAGE

A fuzzy model is being developed for axle fatigue diagnostics. One of the main components of the fuzzy

diagnostic model is the knowledge base as it is shown in Fig. 4. Based on this the fuzzy membership functions and the fuzzy rules can be generated and then modified to give a complete diagnostic model. The variables on the fuzzy model are usually described by a set of member ship functions of different shape such as triangle, trapezoid, Gaussian, etc. where each membership function is uniquely described by a set of critical parameters.

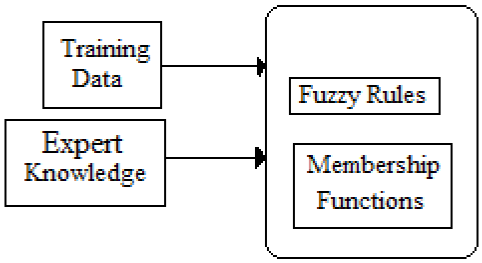

Figure 4. Knowledge base of a fuzzy model

The fuzzy diagnostic model has two primary inputs and a single output. The inputs of the fuzzy diagnostic model are the load stress and the number of cycles of the load stress. The output of the fuzzy model is the cumulative damage on the axle. However, the previous (stored) value of the cumulative damage will also be used as feedback from the output to the input of the model. The block diagram of the fuzzy model is depicted in Fig. 5.

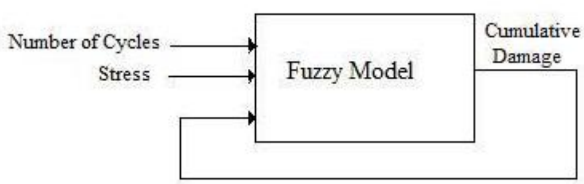

Figure 5. Fuzzy model for fatigue damage

The stress has a threshold value referred to as the normal stress. It is approximately equal to twice of the static stress that is established for the axle. If a stress impact to the axle is lower than the normal stress then there is no need to count the cycles because it is assumed that this sort of stress won't shorten the life time of the axle.

After the cumulative damage has exceeded a certain threshold the fuzzy model of the of the S-N curve for the axle needs to change. This system can be implemented by using a fuzzy automaton. Different sets of If - Then rules can be assigned to different states of the fuzzy automaton. The general block diagram of the Extended Hybrid Fuzzy-Boolean Finite State Machine (HFB-FSM) that was introduced in [7] is shown in Fig.6.

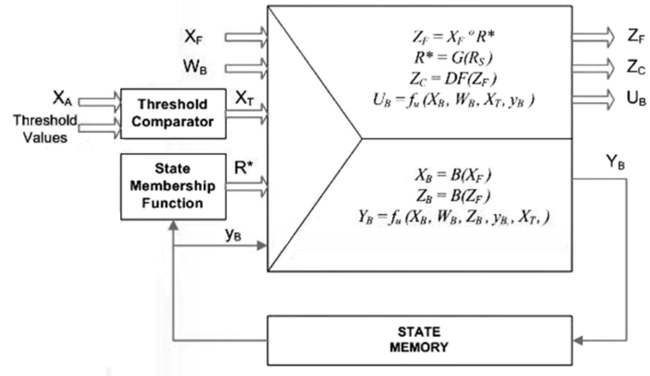

Figure 6. General block diagram of the HFB-FSM fuzzy automaton

The notion of the fuzzy automaton is based upon the following premise: there is an underlying Boolean finite state machine with crisp states in the sense that the machine can stay just in one distinct state at any instant of time. These crisp states are referred to as dominant states for the fuzzy automaton. The fuzzy automaton can stay in more than one crisp state at once, to a certain degree in each. Those degrees are defined by a state membership function. For each fuzzy state there is just one dominant state for which the state membership is a 1 (full membership).

Each dominant state is associated with a linguistic model for inference. For each fuzzy state a composite linguistic model is devised using the linguistic models of those contributing crisp states that has a greater than 0 state membership degree in that fuzzy state. The transitions between fuzzy states are based upon the transitions between their dominant crisp states. The fuzzy inputs (and outputs) are mapped to sets of two-valued logic variables to devise the next states of the two-valued state variables of the underlying Boolean automaton. Two valued outputs are devised using all types of inputs and the current dominant state. Fuzzy outputs are obtained through the compositional rule of inference.

Formally, a fuzzy state is defined by a crisp Boolean state and a state membership function:

$$S_{Fk} : S_k, g_{Sk} \qquad (2)$$

where S_{Fk} stands for fuzzy state k, S_k represents crisp state k, and g_{Sk} is the state membership function associated with S_k. G stands for the matrix of state membership functions.

X_F, W_B, and X_A stand for fuzzy, two-valued (Boolean) and analog inputs with associated threshold values, respectively. The Threshold Comparator Module compares the value of each analog signal with its associated threshold value to set the corresponding X_T signal as true, or false. Z_F, Z_C, and U_B stand for fuzzy outputs, crisp outputs, and two-valued (Boolean) outputs, respectively.

R* is the composite linguistic model (3), and ∘ is the operator of composition. Each crisp state of the HFB-FSM is characterized by an overall linguistic model, R or by a set of linguistic sub-models in the case of multiple-input-single-

output (MISO), and multiple-input-multiple-output (MIMO) systems. For each fuzzy state of the HFB FSM model, a R* composite linguistic model is created from the finite set of R_{Si} overall linguistic models (i=1,..,p). Let the HFB FSM be in fuzzy state S_{Fk}, then

$$R^*_k = \max[\min(\beta^k_1, R_{S1}),\ldots,(\beta^k_p, R_{Sp}) \quad (3)$$

where $\beta^k_1,\ldots,\beta^k_p$ stand for the degrees of state membership function g_{Sk} and $R_{S1},\ldots,R_{Sp}$ are the overall rules in crisp states $S_1,\ldots,R_{Sp}$, respectively. By modifying the β degrees of the state membership functions on-line, new R^* composite linguistic models can be created under real-time conditions.

X_B, Z_B, Y_B, and y_B stand for two-valued Boolean input, Boolean output and next state and present state of the state variables, respectively. B stands for a Fuzzy-to-Boolean transformation algorithm [7] to map a change in the status of a fuzzy variable into state changes of a finite set of corresponding Boolean variables. The Z_C crisp values of the fuzzy outputs are obtained by evaluating a defuzzification strategy, DF.

The transitions between active composite linguistic models are determined by the state transitions of the HFB-FSM. The state transitions of the HFB-FSM are specified by means of a sequence of changes in the states of the fuzzy inputs and outputs, of analog inputs with threshold, as well as of the two-valued inputs. The changes in the states of the fuzzy inputs and outputs are mapped into the corresponding sequence of changes of Boolean input and output variable sets, respectively, using the B algorithm. In this two-valued domain, those changes are joined by the state changes of the two-valued inputs and the true/false of the analog inputs with threshold. This combined Boolean input/output sequence specification is used to synthesize the crisp finite state machine section of the HFB-FSM. Hence, the HFB-FSM model allows the integration of fuzzy, analog and two-valued logic specifications to describe a system's behavior. The integrated treatment of fuzzy, analog with threshold, and two-valued signals is of great importance for designing and modeling complex hybrid systems.

This general model of the HFB-FSM will be customized, i.e., dramatically simplified to adapt to the fatigue damage model for the axle. The cumulative damage input will be used to trigger fuzzy state transitions. The linguistic models have two fuzzy inputs: the stress and the number of cycles, while the single fuzzy output is the cumulative damage. The membership functions are shown in Fig. 7.

The critical parameters of the membership functions are determined using expert knowledge of the S-N curve for axles.

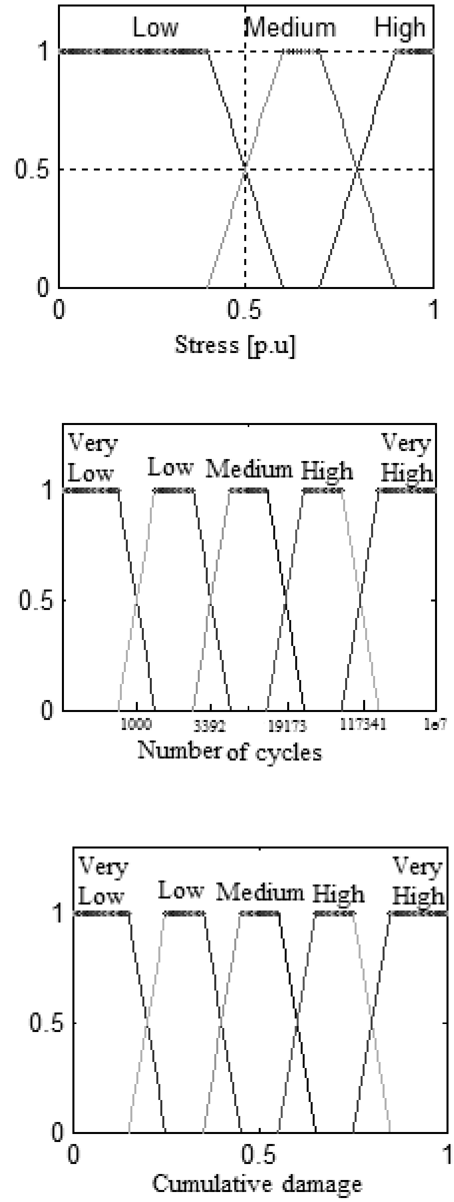

Figure 7. Membership functions for the fuzzy inputs and output

VI. GENERATION OF FUZZY RULES

Initially, the fuzzy If - Then rules will be set up using the domain knowledge of experts and the linear damage model. The generation of the fuzzy rules will be carried out by two operations: cluster extraction and re-clustering.

There are 75 possible combinations of the inputs which yield to 75 clusters. For each cluster there are five possible fuzzy terms of the output (i.e., "Very Low", "Low", "Medium", "High", and "Very High"). The linear damage model will be applied to cluster extraction of the fuzzy rules. This can be done by generating 1000 random data that belong to each cluster. Then the algorithm determines the number of

cycles to failure from the S-N curve and calculates the cumulative damage using the linear damage model. Then it accumulates the number of data points that belong to each output fuzzy term. For example, if the data in of one of the clusters appear as follows in Table I:

TABLE I

TRAINING DATA DISTRIBUTION OF ONE CLUSTER

Inputs			**Output (cumulative damage)**				
Stress	***No. cycle***	***Previous damage***	***Very Low***	***Low***	***Medium***	***High***	***Very High***
Low	Very Low	Very Low	650	300	50	0	0

For this cluster most of the data belong to fuzzy term "VL", Then based upon the "Winner take all" algorithm the fuzzy rule of the cluster will be generated as it is shown in Table II:

TABLE II

RULES EXTRACTED BASED ON THE WINNER-TAKE-ALL MECHANISM

Inputs			**Output (cumulative damage)**	
Stress	***No. cycles***	***Previous damage***	***Fuzzy set***	***Support rate***
Low	Very Low	Very Low	Very Low	65%

The support rate is important for the process when the fuzzy rules are checked for elimination [3]. For example, if there are two rules with different support rates and one of them is to be eliminated then the rule with the lower support rate will be dropped. After the extraction of the rules from the cluster is carried out the algorithm attempts to merge the rules, if it is possible.

The re-clustering operation is used to make sure that the rules extracted from the clusters are effective. In the re-clustering operation the distance between the clusters and the sample data will be calculated [1],[3]. Then the sample data will be re-clustered to the closest cluster. After re-clustering all the data the centers of the clusters will be measured. If the membership functions' parameters are not close to the clusters' centers then the membership function parameters will be modified to adopt better to the clusters' centers.

The modification of the membership functions may change the fuzzy rules because the cluster partitions are changed.

VII. OPTIMIZATION OF FUZZY MEMBERSHIP FUNCTIONS

The re-clustering operation is used to update the critical parameters to the center of the training data clusters in order to improve the fuzzy model's performance with respect to the diagnosis of the axle fatigue.

The objective of the optimization of fuzzy membership functions is to update their critical parameters such that all the training data that belong to the same class should be within the range (y_l, y_u) of the output membership function.

If all the sample data in each class are within the range of the corresponding membership function then the membership function is optimized. Otherwise, the relative distance between the training data and the cluster range must be minimized. The objective function is to update the critical parameters of the membership functions such that to minimize the relative distance between the sample data and the membership functions in the same class.

Lu, Chen, and Hamilton [3] suggested using the stochastic annealing method to optimize the membership functions due to the difficulty of evaluating the first derivative of the object function. Filev [6] used the Levenberg-Marquardt minimization method in multi input and multi output fuzzy diagnostic models.

VIII. CONCLUSIONS

The basic architecture of an Intelligent Vehicle Health Management System (IVHMS) for light tactical vehicles was presented and its objectives are outlined. A fuzzy model was introduced to tackle the problem of diagnosing axle fatigue. The output of the fuzzy model is the cumulative damage to the axle. Based upon the cumulative damage, the level of the axle fatigue can be diagnosed and the remaining life of the axle can be predicted. The linear damage model was used to generate a set of training data for the fuzzy model. Based on the training data, the membership functions and fuzzy rules were modified by using cluster extraction and re-clustering operations. Finally, the critical parameters of the membership functions can be optimized to improve the fuzzy model for axle fatigue diagnostics.

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